Development of a Framework for Asynchronous Periodic Pattern Detection in Multivariate Time Series

A Synopsis

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1. Introduction:

The availability of sophisticated computing devices with high storage and processing speed has led to the computerization of day-to-day operations in most organizations, resulting in large volumes of accumulated data. Data mining, a multidisciplinary field, encompasses such methods and techniques and helps users extract valuable and hidden knowledge from large volumes of data in patterns. (1)

Class/Concept Description

Class/concept description methods mine the general characteristics of one or more data groups. Class characterization and discrimination are the sub-functionalities of class/concept description data mining functionality. Class discrimination derives general characteristics of two or more groups or classes of data. One of the classes is called the target class, and the rest of the classes are called contrasting classes. Class discrimination also compares the target and contrasting classes using interestingness measures.

Association Rule Mining:

Frequent patterns are frequently co-occurring attribute-value pairs in the given dataset. Association rules can be mined from different types of datasets like transactional datasets, relational databases, data warehouses etc. It is extensively used for market basket analysis, where association rules help identify prospective buyers for an item using frequent patterns of items purchased together by many customers.

Classification:

Classification is a supervisory learning technique which builds models based on training data. Classification requires the class label of each object in addition to descriptive attributes. Classification models are used to describe and distinguish the different data classes present in the data.

Clustering:

Clustering is the process of grouping objects such that all the objects belonging to the same group share similar characteristics.

Outlier Analysis

Identification of objects significantly different from the rest is called outlier analysis. The frequency of occurrence of outliers is substantially less compared to normal things. Outlier analysis is essential in specific applications like detecting fraud, economic recession, and natural disasters like earthquakes and floods.

Data Preprocessing: Data mining can generate high-quality patterns provided the data it is applied to is high quality. The data required for analysis may be available from various data sources. Data preprocessing techniques help to overcome these problems. Data integration techniques fetch the data in different databases and convert it into a unified schema. Data transformation techniques transform the data to the form required by the mining algorithm. Data reduction techniques reduce the size of the data by removing redundant and irrelevant attributes, converting it into alternative smaller forms etc. Mining patterns from the reduced representation of data is more scalable, and the patterns mined from reduced expression are more general, interpretable, and valuable. Every real dataset has to be preprocessed before applying data mining.

Identification of Interesting Patterns: The generated patterns or models are post-processed to retain only the accurate and exciting ways. Attractive measures are employed to ensure the controlled patterns' novelty, simplicity, validity and utility. Different data mining tasks use various interestingness measures for evaluating the patterns.

Evolution Analysis

Evolution analysis analyses the data whose state or behavior changes over time. Generally, this includes studying time series, temporal, spatiotemporal and sequence datasets.

A sequence is an ordered list of elements from any domain. The order among the sequence elements may be implied by time order as in time series and temporal datasets, or by physical position as in biological datasets. (2)

(i) Time Series A time series is a sequence of absolute values of the same variable measured over time. Time series data consists of long numerical data sequences recorded at regular intervals. Time series data is generated in many domains like meteorology, economics and scientific, medical and natural observations.

(ii) Temporal Data The elements of temporal datasets can be absolute values or symbols. Examples of temporal datasets are customer shopping sequences, web click streams etc. The sequences where order among the elements is implied by time order are also called event sequences. Each component of an event sequence is called an event. An event e is an observation or attribute-value pair at time t. An event set sequence is a sequence where zero or more events occur at each time instant t. Multivariate time series can be represented as an event set sequence.

(iii) Spatiotemporal Datasets These datasets have both spatial and temporal characteristics. The usage of smartphones, RFID tags and G.P.S. devices has made tracking people, animals and vehicles easy nowadays. This has led to the generation of spatiotemporal datasets. The spatiotemporal dataset has attributes that describe the location, like latitude and longitude, and other attributes observed at a timestamp to produce a multivariate time series. A spatiotemporal dataset can also be represented as an event set sequence.

(iv) Biological Sequences consist of elements where the order among them is implied by position. Examples are gene and protein sequences.

(v) Types of Patterns that can be mined from Sequences: The kinds of patterns that can be extracted from sequence data include frequent episodic patterns, periodic patterns, frequent continuities, etc. Frequent sequential patterns are retrieved subsequences from sequence

databases that are frequently seen. Except for the restriction on the contiguous and disjoint matches, it is comparable to a periodic pattern. (3)

Periodic Patterns

Periodic patterns exist in various datasets like time series, temporal, spatiotemporal and biological datasets. Closing prices of a company's stocks and seasonal changes in the climate of a place are examples of periodic patterns in time series databases. Purchase patterns in retail stores and web click streams show temporal regularity. Movement of planets, migratory animals and daily traffic patterns exhibit spatiotemporal frequency. Periodicity detection in continuous-valued data like continuous time series is often performed using techniques like autocorrelation using Fast Fourier Transforms (FFT), Short Time Fourier Transform (S.F.T.) or FFT together with wavelet transforms (4) (5). In general, continuous-valued data will be discretized for extracting periodic patterns from it. Thus, even if the time series is initially expressed in continuous-valued attributes, it is transformed into a symbolic sequence(s) for extracting periodic patterns. Many algorithms exist that can detect periodic patterns from extended sequences. These algorithms can mine various periodic patterns compared to the ones that work directly on continuous-valued sequences.

Periodic patterns in Symbolic Sequences are classified based on different criteria. Periodic patterns are categorized as frequent periodic and statistically significant patterns based on the frequency of occurrence.

Full and Partial Periodic Patterns A full periodic pattern is a pattern where every element in the pattern exhibits periodicity. (A, B, C) is a full periodic pattern in the sequence given in figure 1.1. The pattern has occurred twice with periodicity three at time instants 1 and 4. A pattern in which some elements do not exhibit periodicity is called the partial periodic pattern. (A,*, C) is a partial periodic pattern occurring thrice with periodicity three at time instants 1, 4 and 7. The second element in the pattern does not exhibit periodicity as indicated by '*' that matches with any symbol.

1	2	3	4	5	6	7	8	9
A	B	C	A	B	C	A	D	C

Figure 1.1 Sequence with full and partial periodic patterns

Perfect and Imperfect Periodic Patterns A perfect periodic pattern is a pattern 'X' that repeats at every p‟ time units/positions starting from the first occurrence of 'X' where p‟ is the periodicity of the pattern. For example, (A,*, C) is a perfect periodic pattern in the sequence given in figure 1.1. It repeats with periodicity 3. If some of the expected occurrences of 'X' miss, then such a pattern is called the imperfect periodic pattern. (A, B, C) is an imperfect periodic pattern in the same sequence. This pattern did not occur at one of the expected positions, i.e. at position 7.

Synchronous and Asynchronous Periodic Patterns

1	2	3	4	5	6	7	8	9	10	11	12
A	B	C	D	B	C	A	B	C	A	B	C

Figure 1.2 Sequence with synchronous periodic pattern

A pattern that occurs periodically without any misalignment is called the synchronous periodic pattern. (A, B, C) is a synchronous imperfect periodic pattern in the sequence given in figure 1.2. (A, B, C) started occurring from position 1 with period 3. It is expected to occur at positions 1, 4, 7, and 10. Patterns whose successive repetitions are misaligned due to some disturbance are called asynchronous periodic patterns. (A, E, *) is an asynchronous periodic pattern in figure 1.3.

1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	E	C	A	E	T	X	Y	A	E	D	A	E	F
B			B					B			B		

Figure 1.3 Multi-event/eventset Sequence

Asynchronous periodic patterns are of three types. They are single-event 1-patterns, multi-event 1-patterns and complex patterns. If only one position in the pattern exhibits periodicity, it is called a singular pattern or one pattern. For example, (A,*,*), (B,*,*) (E,*,*), ((A.B.),*,*) are singular asynchronous periodic patterns found in the sequence given in figure 1.3. There is a disturbance between the second and third occurrences of these patterns. ((AB),*,*) is multi-event 1-pattern. ((AB), E, *) is a complex asynchronous periodic pattern repeating with period 3. Of all the different types of periodic patterns discussed above, asynchronous periodic patterns are a more general category of patterns with maximum applicability.

Applications of Asynchronous Periodic Patterns: (6) Applications like inventory replenishment, changes in the climate, E.C.G. data etc., inherently contain asynchronous periodic patterns. For example, if a store replenishes its inventory at the end of each month, the time between consecutive replenishments is one month. In a particular month, to meet the demand on the occasion of a festival, the store replenishes the inventory on the third week of the month. Later, even if the time gap between every two replenishments is still maintained as one month, the replenishment time shifts to the third week of a month instead of the fourth week of the month. Patterns such as these, whose repetitions are shifted due to some disturbance, are called asynchronous periodic patterns. Synchronous periodic pattern mining algorithms cannot extract such patterns.

1.1 Asynchronous Periodic Pattern Mining Problem

If a pattern repeats more often than or equally as often as a global rep, it is considered to occur significantly in the subsequence. This collection of valid segments is referred to as a valid subsequence, and there is a tolerable disruption between the valid segments. A subsequence of the input sequence that contains the pattern at least min rep times consecutively without any overlaps is considered a valid segment. The greatest permitted disturbance between succeeding valid segments of a pattern is indicated by max disturbances.

1.3 Asynchronous Periodic Pattern Mining Algorithms

Longest Subsequence Identification (LSI) (7), Single Multiple Complex and Asynchronous periodic pattern miner (S.M.C.A.) (6), Linked List structure based One Event One Pattern (O.E.O.P.) algorithm (8) and E.M.A.P. (9) were successful algorithms for asynchronous periodic

pattern mining. LSI can only handle event sequences but not event set sequences. S.M.C.A. overcomes this limitation. It is a four-phase algorithm that detects all the valid subsequences containing each asynchronous periodic pattern. This is the most successful algorithm for mining asynchronous periodic patterns extensively used by several researchers. When compared to S.M.C.A., E.M.A.P. can efficiently mine all patterns in a single step, and a single scan of the sequence provides a very large primary memory is made available. As part of this research work, it was observed that the E.M.A.P. algorithm aborts even for reasonably long event set sequences when min_rep is set low (10). S.M.C.A. also struggles to mine patterns when the average number of events per timestamp exceeds four and min_rep is set low due to the exponentially large segment space to be explored. It was observed that there is an enormously large number of redundant segments associated with generic patterns subsumed by specific patterns. To the best of the knowledge of the author, no existing algorithm can successfully mine asynchronous periodic patterns from event set/multi-event sequence when the average number of events per timestamp is greater than four. A wide variety of applications in the domains such as weather modelling, industrial process monitoring, health informatics, stock market data, E.C.G. data etc., produce multivariate time series with a number of variables well above four and hence call for a framework for extracting asynchronous periodic patterns of unknown periods. In this thesis, the author proposes the synergy of subspace clustering and sequential pattern mining as a solution for asynchronous periodic pattern extraction from long multivariate time series.

1.2 Subspace Clustering

Organizing objects into groups with comparable properties for each group is the process of clustering (1). The similarity between objects is calculated using similarity measures, and the choice of similarity measures depends on the type of objects clustered. For example, the similarity between objects described using numerical attributes is calculated using Euclidean distance, Manhattan distance, Mahalanobis distance etc. The cosine similarity measure is used for vector space data; the Jaccard coefficient is used for binary data etc.

2. Literature Review

Many events in nature and real-life exhibit periodicity. Periodic patterns exist in a number of datasets like time series, temporal, spatiotemporal and biological datasets. Studying periodic patterns helps in understanding the underlying characteristics of sequence data and also in

predicting the future behaviour of data. Owing to a large number of applications, periodic patterns have been extensively studied in the recent past. Many researchers from fields like statistics, data mining and signal processing have contributed a number of techniques to detect periodicity and periodic patterns from data.

2.1 PERFECT AND IMPERFECT PERIODIC PATTERNS

Han *et al.* (1999) developed an algorithm in order to mine whole imperfect periodic patterns and partial, imperfect periodic patterns in two scans of the time series, called max-subpattern hit set. (11)

Aref *et al.* (2004) expanded the max-subpattern hit set by proposing algorithms for incremental, online, and merging mining of partial periodic patterns. (12) It only has to be scanned once again from the old database. Users of the online version of the algorithm are able to alter the thresholds utilized in the mining process while it is still running. The goal of merge mining is to combine patterns extracted from two or more databases. Without having to repeat the mining method, this merging procedure enables us to find patterns in the merged database.

2.2 FULL AND PARTIAL PERIODIC PATTERNS OF UNKNOWN PERIODICITY

There may be patterns in some datasets that repeat for unforeseen lengths of time. The periodic pattern mining algorithm must, in these circumstances, extract prospective periods and the patterns that coexist with the extracted periods.

Ma *et al.* (2001) have made significant advancements in this area by discovering all partial periodic patterns with unidentified periods (13). In order to find partial periodic patterns, two algorithms were created. The first, also known as period first, locate potential periods first before identifying the relationships between each period's occurrences of events.

Dutta *et al.* (2009, 2012) and Mahanta et al. (2008) have suggested algorithms to find both perfect and imperfect calendar-based periodic patterns (14, 15, 16). For a continuous domain, the time complexity of these techniques is O(n log n), whereas, for a discrete domain, it is just O(n).

R. Uday Kiran *et al.* (2015) proposed Recurring patterns in time series data, a new class of partial periodic patterns (17). You can use this technique with an event or events sequences. If a

pattern X appears in at least min Rec time intervals with period p per and there are at least min P.S. repeats of the pattern in each time interval. The pattern is said to be recurrent. A pattern X need not show up in a time span with exact regularity. Additionally, the periodicity of X need not be constant during the time span. The only requirement is that there should be less than per second between each subsequent repetition of the pattern. If the time gap between successive repetitions of the pattern is less than per and the pattern has appeared for at least min P.S. number of times in a given time interval, then the time interval is called an interesting periodic interval of the pattern. A pattern is called a recurring pattern if there are at least a min Rec number of such interesting periodic intervals for it.

2.3 SYMBOL, SEQUENCE AND SEGMENT PERIODICITY

Rasheed *et al.* (2011) used a data structure in string processing, the suffix tree (18). Suffix trees can be used to solve several problems, including the longest common substring between two strings, the substring problem, and exact string matching. All of the suffixes in a string are stored in a suffix tree. There is a distinct path from the string's root to each suffix's matching leaf node in the suffix tree.

M.G. Elfeky *et al.* (2005) created a convolution-based technique for detecting symbols and segmenting periodic patterns (19). For the suggested mapping, the method does a single scan of the time series before converting it to a binary vector. The algorithm's temporal complexity is O(n log n). In mining synchronous periodic patterns, it performs well. When there is insertion and deletion noise, it fails.

2.4 DENSE PERIODIC PATTERNS

Such algorithms won't be able to identify patterns that only appear in limited time series segments due to insufficient evidence or confidence.

It can be challenging for the end user to locate such time series segments that might contain periodic patterns.

Sheng *et al.* (2006) have put out a method for mining dense periodic patterns from time series databases (20). The method extracts dense time series fragments for each distinct symbol. Then,

utilizing only the dense portions of the alphabetic characters, partial periodic patterns are generated using a max-sub pattern tree. By determining the lower bound period for each symbol in each dense fragment, this approach also prunes some periods. Pruning is safe for any durations that fall below the lower bound period.

2.5 APPROXIMATE PERIODIC PATTERNS

Most real-world data is noisy and imprecise. Such as gene mutations in D.N.A. sequences. Hence it is necessary to mine approximative patterns. The previously covered algorithms can mine roughly repeating periodic patterns and can tolerate replacement, insertion, and deletion noise. These techniques enable approximation of the patterns' positions of occurrence. Zhang, M., Kao, B. *et al.* (2007) discussed an approach that enables the approximation of both occurrence places and pattern structure. (21)

2.6 SURPRISING PERIODIC PATTERNS

In some applications, such as those involving seismic data, system traces, credit card transactions, and genetic data, patterns that happen less frequently but more frequently than expected are still thought to be intriguing. However, all of the periodic pattern mining algorithms that have been explored thus far favour mining frequent occurrences of periodic patterns.

Yang *et al.* (2001) devised a method called InfoMiner to mine uncommon but statistically significant periodic patterns (22). A pattern is deemed important if its occurrence frequency significantly outweighs its predicted frequency. Instead of using a support model, a novel model called an information model is employed to find the uncommon and statistically significant patterns. To gauge how surprising a pattern in a data sequence is, information gain is employed as a measure.

2.7 ASYNCHRONOUS PERIODIC PATTERN MINING ALGORITHMS

The various techniques suggested for mining asynchronous periodic patterns are Longest Subsequence Identification (LSI), Single Multi Complex and Asynchronous Periodic Pattern Miner (S.M.C.A.), Linked List structure based One Event One Pattern Miner (O.E.O.P.), and E-MAP.

Yang, J., Wang *et al.* (2003) found that the original algorithm, LSI, creates complicated patterns and single event 1-patterns from event sequences (7). It locates the longest subsequence that includes each asynchronous periodic pattern.

Huang, K.Y. *et al.* (2005) created a four-phase S.M.C.A. algorithm by which asynchronous periodic patterns can be mined (6). Valid segments are mined in the first three phases of the S.M.C.A. for complicated patterns, multievent 1-patterns, and single event 1-patterns, respectively.

Yeh, J.S. *et al.* (2009) used an effective linked list-based data structure to mine all asynchronous periodic singular patterns of all events in a single scan of the series (8). Sirisha, G.N.V.G. *et al.*(2014), and Maqbool, F., Bashir *et al.*(2006) found that for datasets like data streams, it can be used to replace SPMiner from S.M.C.A. SPMiner is more effective and scalable when compared to the O.E.O.P. algorithm (10) (9).

2.8 MULTIVARIATE TIME SERIES DATA ANALYSIS

The majority of subspace clustering algorithms find clusters by mining groups of homogenous objects in a given set of dimensions and/or attributes. Zhao, L. *et al.* (2005), Jiang, D. *et al.* (2004), and Sim, K., Poernomo *et al*. (2010) found that vector data can be handled efficiently using these techniques (23) (24) (25). Kremer *et al.* (2012) put forth a novel paradigm for multivariate time series subspace clustering. According to this concept, a cluster consists of objects or data points that are homogeneous within specific sets of pertinent intervals for each dimension and that together satisfy temporal coherence (26). Kremer et al. (2012) further enhanced the capabilities of this model to address time series misalignments and varying values (27). Individual shifting on the time axis corrects misalignments among time series in a cluster. By permitting a specific percentage of deviating values at each pertinent time point, robustness to deviating values can be established. Since this model is NP-hard, an approximate solution algorithm is suggested.

2.8.1 Time Series Transformation Techniques

These methods for time series representation make it easier to identify trends, forms, and patterns in univariate time series. Although there are numerous methods for representing univariate time series, no one method is adequate for all data mining needs.

Lin, J., Keogh *et al.* (2003) devised an algorithm for Symbolic Aggregate Approximation (SAX) by which a time series is changed into a symbol sequence (28). The time series is first discretized using P.A.A. by the SAX approach. Esmael, B.(2012) created a SAX addition known as Trend,

and Value-based Approximation (T.V.A.) introduces new symbols to indicate the time series' trend (29).

Techniques for representing univariate time series include SAX and T.V.A. Tanaka, Y. *et al.* (2005) found that using the methods, interdependencies and covariations in multivariate time series are more difficult to capture (30). YANGFAN LI *et al.* (2021), according to the author, there is no way to interpret these patterns (31).

Comparative Study

Technique	Advantage	Disadvantage
Periodic-frequent Pattern tree	An efficient technique to mine periodic frequent pattern	Require more search space
MaxCPF- tree	Satisfy downward closure property and solve the problem for a rare item	Computational cost is high
QPF-growth algorithm	Reduce the complexity of time and memory	Do not satisfy downward closure property
PFP-Growth ++ algorithm	Provide a greedy search method to prune frequent non-periodic pattern	Computational cost is high
R.P.- Growth algorithm	Solve the rare item problem	Tree Needs more space and memory

3) Problem Statement

Development of an efficient and effective framework for extracting asynchronous periodic patterns from multivariate time series (event set sequences) by identifying significant combinations of variables of different dimensionalities using the concepts of subspace clustering. The other features of the proposed framework are given below:

1. Uses closed interesting subspaces in the context of density divergence in subspaces of different dimensionalities.
2. Reduces the dimensionality of the multivariate time series without loss of significant information.
3. Eliminates redundant segments for efficiently and effectively extracting asynchronous periodic patterns.

4. Objectives:

The objective of the study are as follows

1) To analyze various subspace clustering algorithms and make a comparative statement of their merits and demerits.
2) To determine the applicability of maximal interesting subspaces for representing multivariate data in the context of density divergence.
3) To investigate various approaches to handle multivariate time series for pattern extraction.
4) To propose the framework for Asynchronous periodic pattern mining algorithms to improve the efficiency of the most successful asynchronous periodic pattern mining algorithm for extracting a non-redundant set of patterns.

5) Plan of Work and Methodology

The literature survey discusses the state-of-the-art techniques on periodic pattern mining, asynchronous periodic pattern mining, subspace clustering, time series representation techniques and conventional periodicity detection algorithms. It also includes a comparative statement of existing asynchronous periodic pattern mining algorithms using stock market data and human genome data.

After this, we will discuss the characteristics of standard real datasets used to evaluate the proposed framework. It discusses in detail the different data preprocessing techniques applied to the datasets. It also includes the architecture diagram of the proposed framework.

We propose the concept of closed interesting subspaces and discuss the methodology for mining closed interesting subspaces from multivariate data. It also discusses the mining of maximal interesting subspaces by SCHISM and modified SCHISM.

6) Conclusion:

This research work will explore various periodic pattern mining algorithms and their merits and demerits in the context of their suitability to multivariate time series periodic pattern mining. Synchronous periodic pattern mining cannot capture the patterns in the presence of disturbances between consecutive occurrences of the pattern. Asynchronous periodic pattern mining, which can capture such patterns, is studied, and different state-of-the-art asynchronous periodic pattern mining algorithms were implemented and compared. S.M.C.A. is found to be the preferred asynchronous periodic pattern miner as it can handle both the event sequences as well as event set (multievent) sequences. It is also capable of mining asynchronous periodic patterns of unknown periodicity. The existing asynchronous periodic pattern mining algorithms, including S.M.C.A., struggle to mine the asynchronous periodic patterns from the multi-event sequence when the average number of events per timestamp is greater than four. These algorithms also fail when a combination of the following conditions are met; the length of the multivariate time series is in order of thousands, the range of periodicities to be mined is more than a hundred or the periodicity at which the patterns are to be mined is in the order of hundreds or above and when min_rep which is used to identify valid segments is set low, as they result in enormously large search space. In addition to scalability reasons, patterns extracted from multivariate time series using S.M.C.A. contains a lot of insignificant/routine information, which needs further screening to focus on really interesting patterns of macro symbols that capture significant interrelationships among the variables of multivariate time series.

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